Research Article

A Novel MILP Model for the Production, Lot Sizing, and Scheduling of Automotive Plastic Components on Parallel Flexible Injection Machines with Setup Common Operators

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In this article, a mixed integer linear program (MILP) model is proposed for the production, lot sizing, and scheduling of automotive plastic components to minimize the setup, inventory, stockout, and backorder costs, by taking into account injection molds as the main index to schedule on parallel flexible injection machines. The proposed MILP considers the minimum and maximum inventory capacities and penalizes stockout. A relevant characteristic of the modeled problem is the dependence between mold setups to produce plastic components. The lot sizing and scheduling problem solution results in the assignment of molds to machines during a specific time period and in the calculation of the number of components to be produced, which is often called lot size, following a sequence-dependent setup time. Depending on the machine on which the mold is setup, the number of units to be produced will be distinct because machines differ from one another. The stock coverage, defined in demand days, is also included in the MILP to avoid backorders, which is highly penalized in the automotive supply chain. Added to this, the proposed model is extended by considering setup common operators to respond to and fulfill the constraints that appear in automotive plastic enterprises. In this regard, the MILP presented solves a lot-sizing and scheduling problem, emerged in a second-tier supplier of a real automotive supply chain. Finally, this article validates the MILP by performing experiments with different sized instances, including small, medium, and large. The large-sized dataset is characterized by replicating the amount of data used in the real enterprise, which is the object of this study. The goodness of the model is evaluated with the computational time and the deviation of the obtained results as regards to the optimal solution.

1. Introduction

Production planning, sequencing, and scheduling are key operations performed by enterprises, and any circumstances or events that affect them strongly influence the supply chain operation in which they are embedded. All these three planning levels are characterized by the decision-making time horizon in accordance with three decision-making levels: strategical, tactical, and operational. Thus, production planning is set at the strategic level by considering families of products, while sequencing and scheduling are set at a more operational decision-making level. Accordingly, Gujjula et al. [1] proposes the following differentiation between these two concepts: (i) production scheduling, which deals with

the assignment of production orders to production intervals with a short planning horizon and specific time periods and (ii) production sequencing, which deals with the sequence of production orders for each production interval.

Our aim is to solve a lot-sizing and scheduling problem with a sequence-dependent setup on parallel flexible machines. To this end, a mixed integer linear program (MILP) model is proposed to minimize the setup, inventory, stockout, and backorder costs by taking into account injection molds as the main index to schedule on parallel flexible injection machines. We also consider setup common operators to extend the proposed basic MILP model.

This article focuses on the specific production lot-sizing and scheduling problem (LSSP) in parallel flexible machines.

According to Kim et al. [2], the LSSP deals with the minimization of production and inventory costs by simultaneously optimizing lot sizes and production schedule. The author also refers to small and big bucket models depending on the number of allowed setups. Accordingly, production scheduling assigns production orders to production intervals with a short-term planning horizon lasting several days or shifts. Moreover, the assignment in the scheduling process has an implicit sequence for each production shift. Therefore, the main goal is to identify the time period when to produce, the quantity to produce as the lot size in units or timeslots, and the production sequence required to meet demand and to avoid backorders and stockouts.

As enterprises are seen as complex systems in operations management, their operation mechanisms are difficult to manage. This difficulty further increases because enterprises belong to a supply network system, in which the complexity and relationships with external actors are latent. Current global market conditions and constant changes in the supply chain environment render enterprises as complex systems. Moreover, researchers have to bear in mind that market consumers are currently used to acquire highly personalized products, which is known as mass customization with short development periods ("time to market").

In the last few years, novel technologies have been increasingly used, such as cloud computing, big data, artificial intelligence, and machine learning. This has become a trend that has boosted companies to transform their way of operating at enterprise and supply chain levels. The result of this digital transformation has been coined as Industry 4.0 [3]. Nevertheless, the application of Industry 4.0 to small- and medium-sized enterprises (SMEs) is not as idealistic as the Industry 4.0 definition indicates. The literature includes different studies on implementing Industry 4.0 technologies into different sectors. The present work focuses on the literature review by Echchakoui and Barka [4], which studies the impact that Industry 4.0 has on the plastics industry. The relevance of the work by Echchakoui and Barka [4] is aligned with the present study because we develop MILP to support the LSSP in a company that belongs to the plastic sector by particularly focusing on the injection of plastic automotive components. In the aforementioned literature review, the authors highlight that implementing Industry 4.0 research into the plastics industry is still in its initial stages, but research in this field is growing.

The origin of this article lies in the H2020 Project Cloud Collaborative Manufacturing Networks (C2NET) [5], whose research focuses on providing a cloud platform, in which a set of tools and technologies are embedded to support: (i) data management and interoperability; (ii) the optimization of plans at enterprise and supply chain levels; and (iii) the integration of collaborative processes among supply network members. The C2NET cloud platform is built according to an open-source philosophy, which makes it affordable and easy to use by SMEs in terms of both monetary and expertise or knowledge required for its use. The optimization module contains advanced optimization models and algorithms to support and calculate replenishment, production, and delivery plans at both the enterprise and network levels. The

calculation of plans at the enterprise level is characterized by only considering the resources and data from a single enterprise, while the calculation of plans at the network level uses the constraints, resources, and data from two supply chain enterprises, or more, as input data. When solving replenishment, production, and delivery plans from a collaborative network perspective, the output data of one enterprise plan are used as the input data of another enterprise plan. If we consider two enterprises from a network, A and B, where A is the supplier and B is the manufacturer, the replenishment plan of company B is constrained by the production plan of company A. Hence, information is exchanged and a loop plan is calculated until the materials required by company B coincide with the materials that can be produced by company A. On the C2NET cloud platform (CPL), the negotiation loop is operated by the collaborative module (COT), the plan calculation is managed by the optimization module (OPT), and data exchange and information interoperability are handled by the data collection framework module (DCF) [6]. The operation and management of the complex large-scale systems that characterize enterprises are covered by the models and tools developed in the CLP with the help of embedded intelligent methods.

Different enterprises from diverse sectors were involved in the C2NET project to validate and test the generated results. The enterprise study object of this article is the automotive industry, which is included in one of the industrial pilots. The automotive supply chain is characterized by the need to perform flexible manufacturing to meet the demand of the original equipment manufacturer (OEM) in terms of delivery time, scheduling, and lot size in a just in time (JIT) production system [7]. When addressing the LSSP in the automotive industry, suppliers are highly penalized when the components supplied to the OEM are delayed. Thus, the automotive components' manufacturers have to manage minimum and coverage stocks to avoid potential penalizations. The coverage goal is set in demand days so that suppliers have to produce at least 3 days of demand in advance (commonly used in the automotive industry) to stock production, as advances to avoid delaying demand because it could imply stopping the automotive assembly line in OEM facilities.

The main objective of this article is to model a real problem from a second-tier supplier in the automotive supply chain and to solve it in a reasonable computation time. Accordingly, a lot-sizing and sequencing model is hereafter provided to respond to the requirements of a second-tier supplier from an automotive supply chain. The proposed optimization model is embedded in the OPT module of the C2NET CPL. A novel MILP model for automotive plastic components production lot sizing and scheduling on parallel flexible injection machines is proposed with setup common operators. The MILP model was implemented in Pyomo [8], used as an extensible python-based open-source optimization modeling language for linear programming and nonlinear programming, among others. Finally, a complex large-scale problem is addressed to deal with the scheduling plan of an automotive components' manufacturer.

The reminder of this document is organized as follows. The next section presents a literature review to gain insight into works that have addressed similar type problems and to justify this study's contribution. Section 3 describes and analyzes the problem to be solved. Section 4 presents the novel MILP model for the automotive plastic components production lot sizing and scheduling on parallel flexible injection machines. We take this MILP as the base model. Section 5 puts forward an extension of the base model, which contemplates common setup operators in the proposed LSSP to provide a more realistic perspective to the base model by taking into account the studied plastic components injection industry. Section 6 offers comprehensive numerical experimentation by considering different data sizes for both proposed models, including small, medium, and large datasets. This article is concluded by discussing the findings obtained with the addressed problem.

2. Related Studies

A large amount of research has been conducted into different LSSP characteristics, but very few studies present optimization approaches that combine or integrate LSSP characteristics, that is, lot sizing and scheduling. According to Ríos-Solís et al. [9], the product-part-mold-machine (PPMM) problem and the part-mold-machine (PMM) problem study this combination of approaches and indicate that this problem type is scarcely addressed in the literature. Ríos-Solís et al. [9] define products as final products and parts as components that derive from the bill-of-materials parts explosion. Furthermore, Ríos-Solís et al. [9] classify the PPMM as bilevel capitated LSSP. Accordingly, the first part of the PPMM and PMM lot-sizing and scheduling problems seeks to determine the optimal size of either a lot of products in the PPMM approach or the parts in the PMM approach. Both approaches seek to assign parts or pieces to molds and molds to the machines. The second part is involved in the scheduling that aims to determine the order of processing molds in machines during each planning time period.

Studies such as Ibarra-Rojas et al. [10] address the problem of manufacturing parts that are produced in molds and are mounted on machines. This study proposes an MILP that seeks to maximize the production of parts and also determines the batch size of every part and the assignments of parts to mold and machines. An update of this study is that proposed by Ríos-Solís et al. [9], which aims to determine the lot size of a finished product; that is, it determines the number of finished products to be manufactured, the number of parts to be manufactured, and the assignment of the parts to the mold and the mold to the machine. The model of Ríos-Solís et al. [9] also contemplates the feasibility of scheduling molds in machines during each period. However, in their experimental results, they only handle one period of time periods and propose working with multiple time periods as a future research line. Different approaches have been proposed in the literature to optimally solve scheduling in engineering; in this regards, Li et al. [11] highlight the importance on the use and application of MILP

to deal with the aforementioned problem in the engineering research area.

Studies about LSSP are paid more attention by researchers and companies, given their applicability to the real world [12]. In our literature review, we find studies that integrate batch sizing decisions into restrictions for scheduling problems (see Table 1), studies such as that presented by Stadtler [13], in which a combined approach to support a single machine LSSP is proposed. For this purpose, an MILP is formulated to minimize maintenance and inventory setup costs over a planning horizon. Wolosewicz et al. [15] combine production planning and scheduling by proposing an MILP that seeks to determine the lot size for a fixed sequence of operations in the machines, taking into account the times and operating costs. Kim et al. [2] present a combined approach in a MILP that seeks to minimize the sum of the cost of production, installation, and inventories. James and Almada-Lobo [16] present an MILP for the scheduling problem and capacitated lot sizing of a single machine and a parallel machine with sequence-dependent setup times and costs. Meyr and Mann [14] put forward an MILP to simultaneously determine production lot sizes and schedules on nonidentical parallel production lines.

Our model deals with the problem contemplated by Ríos-Solís et al. [9] and Ibarra-Rojas et al. [10]. By continuing with the future research lines indicated by these authors, our study considers many periods when modeling and running experiments to solve the LSSP. The base model herein proposed also bears in mind stock coverage constraints, which are typical in the studied automotive supply chain industry context. The proposed novel MILP also contemplates an objective function based on the assembly line and allows idle times among molds, which is a fundamental characteristic for real cases and has been ignored by former studies. Finally, the base model is extended by offering a scenario that comes closer to reality by considering another index that represents the workers who change molds and, thus, bears in mind the casuistry associated with the LSSP that refers to the setups of the usual operators.

3. Problem Description

The main aim of this article is to propose a novel MILP model for the production scheduling carried out by an automotive plastic components manufacturer that acts as a second-tier supplier in the automotive supply chain. Plastic components are produced in molds that are mounted on parallel flexible injection machines. Injection machines shape plastic pellets into automotive semifinished products to then be assembled on an OEM production line. Nevertheless, for industry, studying car components is treated as the second-tier supplier's end products.

According to Ríos-Solís et al. [9], lot-sizing and scheduling plans of mold-injection enterprises entail decision making to determine (i) the lot size as the amount of components to be produced during a period of time or a number of periods to produce the same component and (ii) the assignment of molds to machines by considering that

TABLE 1: Literature review of recent lot-sizing and scheduling problems.

Authors	Objectives	Industrial application	Resolution methods	Solver
Kim et al. [2]	Minimize the sum of production, setup, and inventory costs	Zinc refinery	Heuristic algorithm combining a decomposition scheme with a local search procedure	CPLEX
Ibarra-Rojas et al. [10]	Maximize the weighted cost of produced pieces	Automotive, consumer goods, and toys	Decomposition approach	CPLEX 11.2
Stadtler [13]	Minimize the sum of inventory holding and setup costs in the planning interval	Pharmaceutical		Xpress-MP
Ríos-Solís et al. [9]	Maximize the profit of finished products	Automotive, consumer goods, and toys	Iterative heuristic based on mathematical programming	Gurobi 6.05
Meyr and Mann [14]	Minimize inventory holding, sequence-dependent setup, and line-specific production costs of potentially heterogeneous production lines	—	Decomposition-based approach	GLPK 4.44
Wolosewicz et al. [15]	Minimize the sum of production, inventory, and setup costs	—	Lagrangian heuristic	XPRESS-MP

components can be produced only in specific molds with their shape cavity.

The second-tier supplier herein studied is characterized by having specific molds that produce each automotive component. When two molds are available to produce the same component, these molds involve different processing times, given their technical particularities. Each mold can also be setup on different machines to produce the same automotive component, but the same mold mounted on different machines has different production rates depending on the machine on which it is setup. Accordingly, productivity differs depending on the mold and machine assignment (see Figure 1). Moreover in the automotive sector, two different parts are produced in the same mold, including right- and left-hand parts, which is known as biproduct injection molding [17].

The studied enterprise has 21 injection machines and a set of molds to produce the range of components delivered to the first-tier supplier and finally to the various OEMs that belong to different automotive supply chains, depending on the car brand. The enterprise works three shifts per day over a 5-day week and reserves overtime shifts on the sixth weekday in the event of production not finishing during the normal operation time. Workers are told that they will work overtime periods at least 1 week beforehand.

Molds are changed using cranes and, therefore, a setup time is incurred. A limited number of workers are in charge of changing and mounting molds to the assigned machines. Moreover, these workers, known as setup common operators, work only two of the three shifts that the enterprise arranges.

One of the requirements of the enterprise's study is that once the mold is setup on a machine, the mold should remain for at least 24 h so as not to saturate the work of the limited setup common operators and to not incur on too many setups because the setup time is estimated between 1 and 3 h, which obviously has an associated setup cost. If a longer production time is needed, the mold is set up during the required time periods without incurring any setup costs. Thus, the modeled problem should contemplate no setup carry-over cases.

Backorders are highly penalized in the automotive supply chain. Therefore, enterprises in the automotive industry use stock coverage, which indicates the number of demand days that stocks can cover. Normally in the automotive industry, stock coverage is set at 3 demand days; for example, for the demand of four units for the next three periods ($d1 = 4$ units, $d2 = 4$ units, $d3 = 4$ units), stock coverage is defined as 12 units at the end of the first period. Moreover, as warehouses have space limitations, a maximum inventory is considered.

With regards to the demand, the automotive industry updates the demand during each period for the next five frozen periods. The OEM works with considerable demand information (1 year of demand horizon), but only communicates the demand for the next 6 months to the first-tier supplier. Finally, first- and second-tier suppliers normally work to a 3-month demand horizon and with daily periods. The LSSP considers a 21-day horizon.

A detailed flowchart of the processes is presented (see Figure 2), from the generation of the customer demand to the final resolution of the second-tier supplier model. Accordingly, in the automotive supply chain, the OEM generates customer orders, according to the final customer demand. The OEM transforms the customer orders into the master production scheduling (MPS), which, jointly with bill of materials (BOM) and the inventory availability, computes the material requirement plan (MRP). The OEM demand plan is generated from the MRP and transferred to the first-tier supplier. Then, the first-tier supplier obtains its demand by using a simple bill-of-materials parts explosion, given the OEM demand plan. The second-tier supplier estimates the component requirements from the final requirements in a frozen sequence transferred by the first-tier supplier, and the demand plan is generated [18]. Then, the second-tier supplier proceeds to compute the LSSP model with the aim of (i) assigning molds to machines; (ii) scheduling the processing molds in machines during each planning time period; and (iii) calculating the optimal lot size of products. The LSSP is modeled by considering molds to be the main index. The
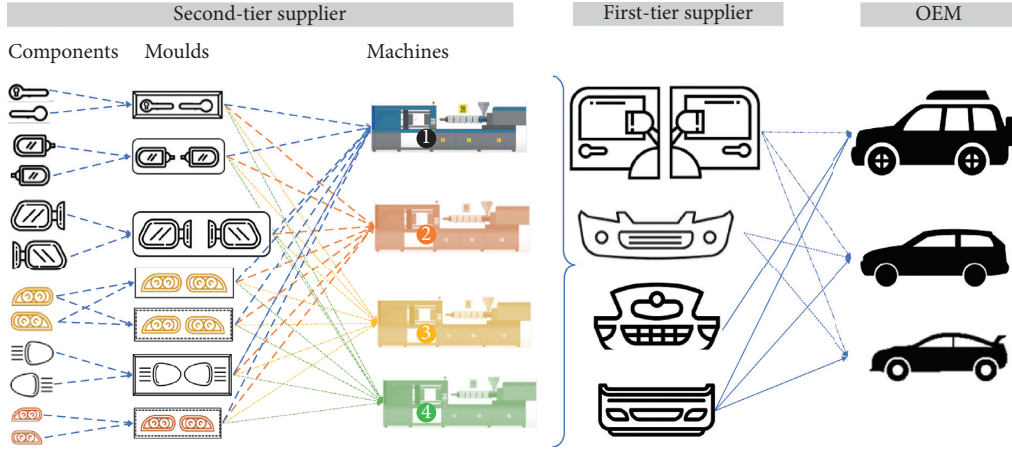
FIGURE 1: Production scheme on parallel flexible injection machines of plastic components in the automotive supply chain.

proposed production lot-sizing and scheduling base model has as main inputs the data parameters described in Table 2. Nevertheless, if setup common operators are considered when solving the LSSP, data parameters related with the type of operators have to be taken into account for building the extended version of the base model. Finally, the proposed MILP is solved by the second-tier supplier using the Guroby solver obtaining optimal or near optimal solutions of the production LSSP. In a nutshell, the objective of the proposed MILP is to minimize the total costs, namely, setup and inventory costs, penalization costs for coverage stockouts, backorder, and tool setup costs, such as the route cost of selecting one machine or another to setup a tool.

4. MILP Model for Lot Sizing and Scheduling on Parallel Flexible Injection Machines: Notation and Model Formulation

The lot sizing and scheduling on the parallel flexible injection machines problem under study is notated in Table 2, where the main indexes related to machines, tools, products, and periods are notated. The input data parameters are presented, and decision variables are established as the output data of the MILP model for lot sizing and scheduling on parallel flexible injection machines.

The formulation of the MILP model for lot sizing and scheduling on parallel flexible injection machines is described next. The objective function minimizes total costs, including setup and inventory costs, penalization costs for coverage stockouts, backorder, and tool setup costs, such as the route cost of selecting one machine or another to set up a tool.

$$
\begin{aligned}
\text{Min } z = &\sum_i \sum_j \sum_t cs_j \cdot \text{SA}_{ijt} + \sum_k \sum_t ci_k \cdot \text{INV}_{kt} \\
&+ \sum_k \sum_t cst_k \cdot \text{ST}_{kt} + \sum_k \sum_t cb_k \cdot B_{it} \\
&+ \sum_i \sum_j \sum_t r_{ij} \cdot cr_{ij} \cdot \text{SA}_{ijt}.
\end{aligned} \tag{1}
$$

It is subject to

Sequence constraints

$$
S_{ijt} \leq r_{ij}, \quad \forall i, j, t, \tag{2}
$$

$$
\text{SA}_{ijt} \leq r_{ij}, \quad \forall i, j, t, \tag{3}
$$

$$
\sum_j S_{ijt} \cdot r_{ij} \leq 1, \quad \forall i, t, \tag{4}
$$

$$
\sum_i S_{ijt} \cdot r_{ij} \leq a_j, \quad \forall j, t. \tag{5}
$$

Constraints (2) and (3) constrain only setup tools j on previously assigned specific machines i. Constraint (4) determines that one or any tool j can be set up for production during each time period t. Constraint (5) guarantees that the total amount of tools j available for production can only be set up as a maximum during each time period t.

4.1. Production and Capacity Constraints.

$$
X_{kt} <= \sum_i \sum_j p_{kt} \cdot r_{ij} \cdot \text{TP}_{ijt}, \quad \forall k, t, \tag{6}
$$

$$
Xnp_{kt} <= \sum_j \sum_i np_{jk} \cdot r_{ij} \cdot \text{SA}_{ijk}, \quad \forall k, t, \tag{7}
$$

$$
X'_{kt} = X_{kt} - Xnp_{kt}, \quad \forall k, t, \tag{8}
$$

$$
\text{TP}_{ijt} = tp_t \cdot S_{ijt}, \quad \forall i, j, t. \tag{9}
$$

Constraint (6) computes the amount of product k produced during time period t and ensures that a specific tool j is able to be set up on machine i during time period t when product k is produced. Constraint (7) determines the amount of products k no longer produced when tool j is set up during time period t on machine i by considering that another tool j is set up on machine i during time period $t - 1$. This also ensures that such a specific tool j is able to be set up on machine i during time period t when product k is produced. Constraint (8) computes the amount of product k
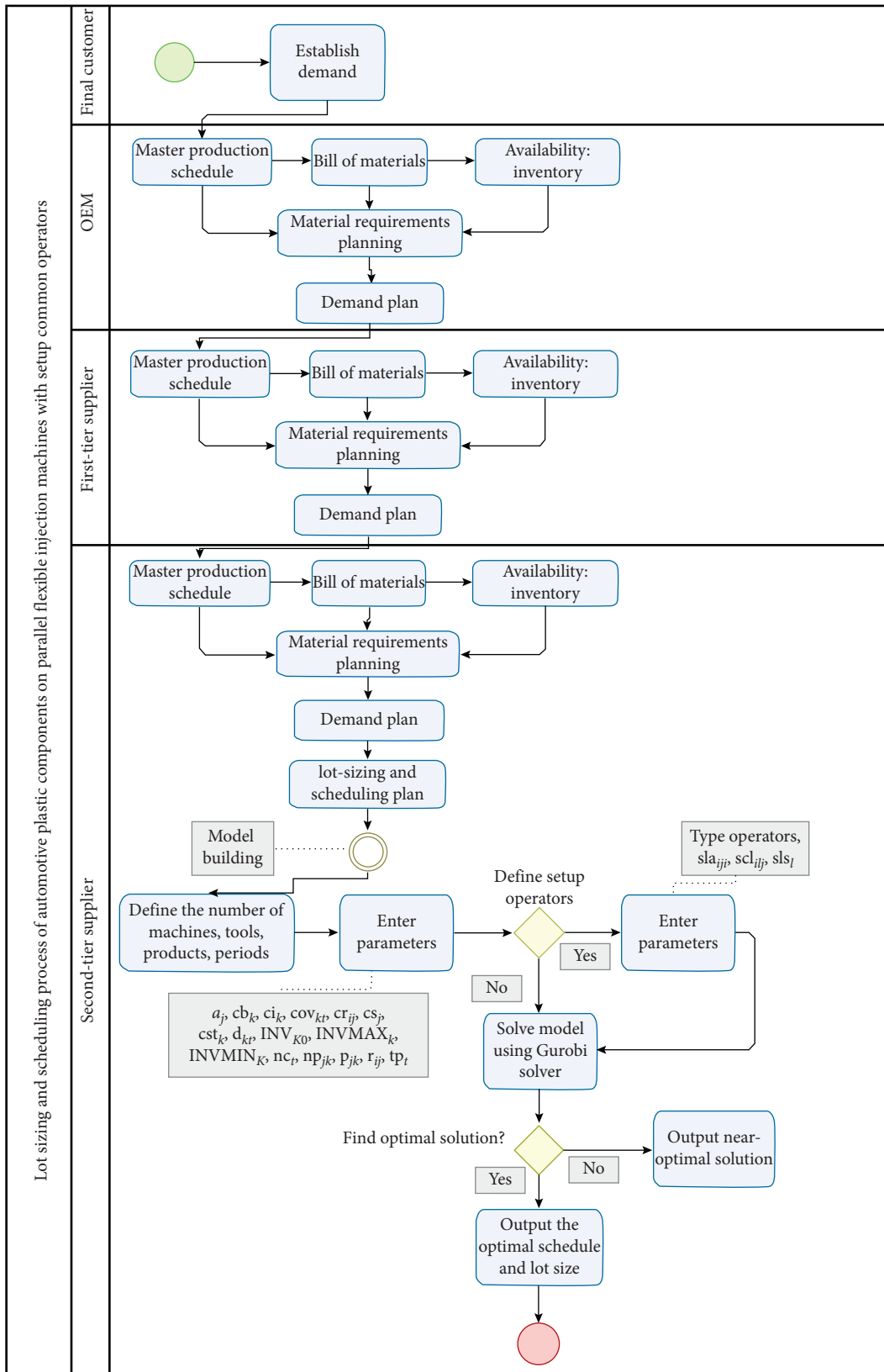
Figure 2: Flowchart of the proposed solution methodology.

TABLE 2: Nomenclature for the model.

Index	
i	Index of machines $i \in \{1, \ldots, I\}$
j	Index of tools $j \in \{1, \ldots, J\}$
k	Index of products (parts) $k \in \{1, \ldots, K\}$
t	Index of time periods $t \in \{1, \ldots, T\}$
Data	
a_j	Total amount of tools j available for production
cb_k	Backorder cost of product k
ci_k	Inventory cost of product k
cov_{kt}	Stock coverage defined as the number of time periods for the stock minimum coverage of product k during time period t
cr_{ij}	Setup cost of tool j on machine i
cs_j	Setup cost of preparing tool j
cst_k	Coverage stockout cost of product k
d_{kt}	Demand of product k during time period t
INV_{k0}	Initial inventory of product k
$INVMAX_k$	Maximum inventory units for product k during time period t
$INVMIN_k$	Minimum inventory units for product k during time period t
nc_t	Amount of tool changes allowed during time period t
np_{jk}	Amount of products k no longer produced when tool j is set up
p_{jk}	Amount of products k produced when tool j is set up
r_{ij}	1 if tool j can be set up on machine i; 0 otherwise
tp_t	Production time available during time period t
Decision variables	
B_{kt}	Backorder of product k during time period t
INV_{kt}	Inventory level of product k at the end of time period t
SA_{ijt}	1 if tool j is set up on machine i during time period t and is not set up on machine i during time period $t-1$; 0 if tool j is set up on machine i during time period $t-1$
S_{ijt}	1 if tool j is set up on machine i during time period t; 0 otherwise
$ST_{kt}t$	Coverage stockout of product k during time period
TP_{ijt}	Production time of tool j set up on machine i during time period t
X_{kt}	Amount of product k to produce during time period t
Xnp_{kt}	Amount of product k no longer produced during time period t, while a tool is set up
X_{kt}'	Amount of product k to produce during time period t by subtracting Xnp_{kt}

to be produced during time period t by subtracting Xnp_{kt} as the amount of products k no longer produced when tool j is set up. Constraint (9) determines the production time used during time period t when tool j is set up on machine i. In TP_{ijt}, we indicate the production lot size during period times, e.g., 24 h. This means that if tool j is set up on machine i, the tool cannot be changed by another one for the next 24 h. Therefore, the minimum lot size corresponds to the products produced during the 24 h that tool j is set up on machine i.

4.2. Setup Constraints.

$$SA_{ijt} = S_{ijt}, \quad \forall i, j, t = 1, \tag{10}$$

$$SA_{ijt} \geq S_{ijt} - S_{ijt-1}, \quad \forall i, j, t > 1, \tag{11}$$
$$SA_{ijt} \leq 1, \quad \forall i, j, t > 1,$$

$$\sum_i \sum_j SA_{ijt} \leq nc, \quad \forall t. \tag{12}$$

Constraint (10) allows the first setup of tool j to be determined on machine i, which enables it to be modeled if tool j is set up during time period t on machine i for the first time, and decision variables S_{ijt} and SA_{ijt} take the same value

1. Constraint (11) ensures that SA_{ijt} does not take values above 1. Constraint (12) limits the amount of tool changes allowed during time period t.

4.3. Inventory Balance Equations.

$$INV_{kt} = INV_{i0} + X_{kt}' - d_{kt} + B_{kt}, \quad \forall k, t = 1, \tag{13a}$$

$$INV_{kt} = INV_{kt-1} + X_{kt}' - d_{kt} + B_{kt} - B_{kt-1}, \quad \forall k, t > 1. \tag{13b}$$

Inventory balance equations (13a) and (13b) guarantee appropriate values for the inventories, quantities to produce, and backorders for each time period $t = 1$ and $t > 1$, respectively.

4.4. Stock Coverage Constraint.

$$INV_{kt} \geq INVMIN_{kt}, \quad \forall k, t, \tag{14}$$

$$INV_{kt} \leq INVMAX_{kt}, \quad \forall k, t, \tag{15}$$

$$\text{INV}_{kt} + \text{ST}_{kt} \geq \sum_{c=1}^{c=\text{cov}} d_{k(t+c)}, \quad \forall k, t < T - \text{cov}. \quad (16)$$

Constraints (14) and (15) limit the inventory levels for each product k according to the available space for inventory holding during time period t. Constraint (16) is a constraint for the stock coverage of products.

4.5. Bound and Nature Variables.

$$\text{SA}_{ijt}, S_{ijt} \in \{0, 1\}, \quad \forall i, j, t, \quad (17)$$

$$X_{kt}, \text{INV}_{kt}, B_{kt}, \text{ST}_{kt}, \text{Xnp}_{kt}, \text{BX}'_{kt} \in \mathbb{N}, \quad \forall k, t, \quad (18)$$

$$\text{TP}_{ijt} \in \mathbb{N}, \quad \forall i, j, t. \quad (19)$$

Constraint (17) indicates the binary nature of setup S_{ijt} and the setup amount SA_{ijt} variables. Constraints (18) and (19) indicate the continuous nature of the represented variables.

5. MILP Model for Lot Sizing and Scheduling on Parallel Flexible Injection Machines with Setup Common Operators: Notation and Model Formulation

The MILP model for lot sizing and scheduling on parallel flexible injection machines described in the previous section provides a solution to an LSSP that emerged in a second-tier supplier of a real automotive supply chain. In this section, the base model is extended by considering setup common operators to respond and fulfill the constraints that arise in automotive plastic enterprises. In this regard, the base model is extended to offer coming closer to reality by considering another index which represents the workers who change molds. It also bears in mind the casuistry associated with the LSSP problem that refers to setup common operators.

The nomenclature for the extended model is represented in Table 3. In order to avoid repetitions, the data and decision variables used for the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators are considered to be the same as in the base model. Table 3 only shows the new data and decision variables in relation to the previous base model. There are different types of operators and a distinct number of workers corresponding to each operator type. For example, let us consider only one setup operator type that corresponds to the qualified technician category and is specialized in changing molds. Companies have a setup operator type corresponding to the auxiliary technician category, whose task involves helping the qualified technician, as well as a setup operator type corresponding to the mechanic category, and provides support whenever failure of a mechanic, electric, or physical, among others, occurs. All these categories or operator types have varying numbers of workers who go on different shifts. For example, in a company like that herein studied that has 21 machines, there could be two

qualified technicians, four auxiliary technicians, and one mechanical technician per shift.

The formulation of the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators is described next. The objective function minimizes total costs, which include setup costs with common setup operators, inventory costs, penalization costs for coverage stockouts, and backorder and tool setup costs, such as the route cost of selecting one machine or another to set up a tool.

$$\begin{aligned} \text{Min } z = &\sum_i \sum_l \sum_j \sum_t cs_j \cdot \text{SA}_{iljt} + \sum_i \sum_l \sum_j \sum_t slc_{iljt} \cdot \text{SA}_{iljt} \\ &+ \sum_k \sum_t ci_k \cdot \text{INV}_{kt} + \sum_k \sum_t cst_k \cdot \text{ST}_{kt} \\ &+ \sum_k \sum_t cb_k \cdot B_{it} + \sum_i \sum_l \sum_j \sum_t r_{ij} \cdot cr_{ij} \cdot \text{SA}_{iljt}. \end{aligned}$$

$$(20)$$

It is subject to the following.

5.1. Sequence Constraints.

$$S_{iljt} \leq r_{ij}, \quad \forall i, l, j, t, \quad (21)$$

$$\text{SA}_{iljt} \leq r_{ij}, \quad \forall i, l, j, t, \quad (22)$$

$$\sum_j S_{iljt} \cdot r_{ij} \leq 1, \quad \forall i, l, t, \quad (23)$$

$$\sum_i S_{iljt} \cdot r_{ij} \leq a_j, \quad \forall j, t, l. \quad (24)$$

Equations (21) and (22) constrain only setup tools j by setup operators l on specific previously assigned machines m. Constraint (23) determines that one or any tool j can be set up by setup operator l for production during each time period t. Constraint (24) guarantees that the total amount of tools j available can only be set up for production as a maximum during each time period t by setup operator l.

5.2. Production and Capacity Constraints.

$$\text{Xnp}_{kt} < = \sum_i \sum_l \sum_j np_{jk} \cdot r_{ij} \cdot \text{SA}_{iljk}, \quad \forall k, t, \quad (25)$$

$$\text{TP}_{ijt} = tp_t \cdot S_{iljt}, \quad \forall i, l, j, t. \quad (26)$$

Constraint (25) determines the amount of products k no longer produced when tool j is set up by operator l on machine I during time period t by considering that another tool j is set up on machine i during time period $t-1$. It also ensures that such a specific tool j can be set up on machine i during time period t when product k is produced. Constraint (26) determines the production time spent during time period t when tool j is set up by operator l on machine i.

TABLE 3: Nomenclature for the model.

Index	
l	Index setup-type operators $l \in \{1, \ldots, L\}$
Data	
sla_{ilj}	Number of setup-type operators l required to setup the tool j on machine i
scl_{ilj}	Cost of type operator l to setup the tool j on machine i
sls_l	Number of available workers of type operator l available
Decision variables	
S_{iljt}	1 if the tool j is setup by setup operator l on machine i during time period t; 0 otherwise
SA_{iljt}	1 if tool j is set up by setup operator l on machine i during time period t and is not set up on machine i during time period $t-1$; 0 if tool j is set up by setup operator l on machine i during time period $t-1$

5.3. Setup Constraints.

$$SA_{iljt} = S_{iljt}, \quad \forall i, l, j, t = 1, \tag{27}$$

$$SA_{iljt} \geq S_{iljt} - S_{iljt-1}, \quad \forall i, l, j, t > 1,$$
$$SA_{iljt} \leq 1, \quad \forall i, l, j, t > 1, \tag{28}$$

$$\sum_i \sum_j SA_{iljt} \leq nc_t, \quad \forall l, t. \tag{29}$$

Constraint (27) allows the first set up of tool j performed by operator l on machine i to be determined and enables it to be modeled if tool j is set up during time period t on machine i for the first time. Decision variables S_{iljt} and SA_{iljt} take the same value 1. Constraint (28) ensures that SA_{iljt} does not take values above 1. Constraint (29) limits the amount of tool j changes allowed during time period t and set up by operator l on machine i.

5.4. Labour Constraint.

$$\sum_i \sum_j SA_{iljt} \cdot sla_{ilj} \leq sls_l, \quad \forall l, t. \tag{30}$$

Constraint (30) limits the amount of tools changes allowed during time period t to the available number of workers of type operator l by considering the number of setup-type operators l required to set up tool j on machine i.

5.5. Bound and Nature Variables.

$$SA_{iljt}, S_{iljt} \in \{0, 1\}, \quad \forall i, l, j, t. \tag{31}$$

Constraint (31) indicates the binary nature of the setup S_{iljt} and setup amount SA_{iljt} variables. Finally, the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators is also subject to constraints (6), (8), (13a), (13b), (14)–(16), (18), and (19).

6. Case Study and Computational Experiments

The proposed base MILP model for lot sizing and scheduling on parallel flexible injection machines and the extended MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators was implemented in Python 3.8.2, using Pyomo [8] as an extensible python-based open-source optimization modeling language for linear programming. The performance of the proposed model was evaluated on a set of instances that reflect different characteristics of the real-world case of the automotive components industry under study. All the numerical tests were performed on a personal computer equipped with an Intel (R) Core (TM) I5-8500 @ 3.00 GHz Processor and 8 GB RAM. We used Python 3.8.2 and tested applying Gurobi 9.0, to solve the mixed integer linear programming model.

In the next section of data generation, it is described how the data are generated to run the computational experiments. The datasets generated to validate the proposed models correspond to small, medium, and large datasets. Sized datasets can be accessed through a link available at the end of the document. Finally, the last section presents the results of the computational experiments carried out.

6.1. Data Generation.
For the data generation, we define various instance sets, including small, medium, and large data sizes. The small dataset corresponds to the minimum amount of data required to test the proposed model; the medium dataset allows to test the model with a reasonable number of parameters and variables to be solved by the model, approaching to the realistic view of the LSSP; and finally, the large dataset replicates the real amount of data managed by real world enterprises when solving the LSSP. For the computational experiments, all the datasets are built through considering the parameter values depicted on Table 4. The data values are created in the way that mostly represents real data from the automotive components industry; next, the data values are defined:

(i) The parameter a_j determines the total amount of tools j available for production; in this regard, only one unit of each tool is available, and this means that there are not duplicated tools to produce the same components.

(ii) The backorder cost (cb_k) and the coverage stockout cost (cst_k) are represented by a very high value (equal to M (99999)) in order to avoid customer missing parts in the model resolution.

(iii) Inventory costs (ci_k) are set with values uniformly distributed in given interval; $U(u_1, u_2)$ is a random variable which is uniformly distributed on $[u_1, u_2]$.

(iv) The stock coverage is defined in three days of demand. Nevertheless, in small datasets where the

TABLE 4: Generation of value for data parameters.

Parameter	Value
a_j	1
cb_k	99999
ci_k	$U\,(0.1, 1)$
cov_{kt}	1 when $T < 3$; Otherwise, 3 when $T > 3$
cr_{ij}	Random (5, 15)
cs_j	Random (45, 50)
cst_k	99999
d_{kt}	Random (15, 40) if $T =$ first 5 periods of the week; Otherwise, 0 if $T = 6^{th}$ and $T = 7^{th}$ periods of the week
INV_{k0}	1
$INVMAX_k$	Random (10000, 20000)
$INVMIN_k$	1
nc_t	Random $(I, I + 5)$ 0 if $T = 7^{th}$ period of the week
np_{jk}	Random (2, 5)
p_{jk}	Random (2, 5)
tp_t	24 hours if $T =$ first 5 periods of the week 16 hours if $T = 6^{th}$ period of the week 0 hours if $T = 7^{th}$ period of the week
r_{ij}	1
sla_{ilj}	1
scl_{ilj}	$U\,(2.5, 3.5)$
sls_l	I

number of periods is lower than three, we have considered one coverage day of demand ($cov_{kt} = 1$) in order not to have unfeasible solutions in the model resolution, in such a way that the model considers one period of future demand (d_{t+1}) to be produced during period t.

(v) Random $[r_1, r_2]$ values denote a random integer value over the interval from r_1 to r_2. The following data parameters use Random $[r_1, r_2]$ values: setup cost of a tool (cr_{ij}), setup cost of preparing a tool (cs_j), maximum inventory ($INVMAX_k$), and the amount of products no longer produced when a tool is set up (np_{jk}),

(vi) The amount of products produced when a tool is set up (p_{jk}) is also denoted as Random $[r_1, r_2]$. In this regard, $p_{jk} > 0$ indicates that product k is assigned to the tool j; otherwise, $p_{jk} = 0$. Parts are randomly assigned to tools, with the condition that each part must be assigned to one tool. Table 5 proposes an example of assignment on a small dataset composed of three tools and six products.

(vii) In order to generate the values for the demand, blocks of seven time periods corresponding to the 7 days of the week are considered. In this regard, the first fifth periods of the week will have demand values set as Random (15, 40); otherwise, $d_{kt} = 0$ on the sixth and seventh periods of the week, that is, on Saturday and Sunday.

(viii) The minimum inventory ($INVMIN_k$) is set as one unit for all the products k; accordingly, the initial

inventory (INV_{k0}) is also set as one unit for all products k.

(ix) The amount of tool changes allowed (nc_t) is defined by Random (I, $I + 5$), with I being the minimum number of machines changes allowed, that coincides with the total number of machines. Considering the same scheme of blocks of weeks divided in 7 periods, no tool changes are allowed in the 7th period of the week, $nc_t = 0$; this is because on Sundays, the enterprise does not produce and uses it as a day of rest or for machine maintenance, etc.

(x) According to this last statement, the time available for production (tp_t) is 24 hours for the first 5th periods of the week and 16 hours for the 6th period of the week. No time production is available for the 7th period of the week.

(xi) $r_{ij} = 1$ indicates that all the tools can be setup on all the machines.

The aforementioned parameters and values are defined for the base model. The three parameters added for the extended model, which considers set up common operators, are described below (see Table 4):

(i) $sla_{ilj} = 1$ indicates that one setup-type operator is required to setup the tool j on machine i

(ii) The cost of type operator l to setup the tool j on machine i (scl_{ilj}) is set with values uniformly distributed in the given interval; $U(u_1, u_2)$ is a random variable which is uniformly distributed on $[u_1, u_2]$

(iii) Finally, the number of available workers of type operator l available (sls_l) must be as much as the number of machines I

In addition, we attach the link to the synthetic data generator, so that the model can be reproduced in future research; https://bit.ly/3iwfObA.

6.2. Results and Computational Experiments. Using the synthetic data generator mentioned above, a set of experiments have been conducted to validate the two proposed models: (i) a base LSSP model, an MILP model for lot sizing and scheduling on parallel flexible injection machines and (ii) an extended LSSP model, an MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators.

In order to give the reader a clear insight of the input data parameter values and the output data results once implemented the proposed MILP, we include an example of a small dataset size. The input data for the base LSSP model are presented at https://bit.ly/3p3IFqo. The small dataset of the base model is characterized by having 2 machines, 4 tools, 6 parts, and 3 periods. The results obtained with the decision variables in the MILP model for lot sizing and scheduling on parallel flexible injection machines are presented in Tables 6 and 7.

According to the results obtained in the MILP model for lot sizing and scheduling on parallel flexible injection

TABLE 5: Amount of products produced when a tool is set up.

j	k	p_{jk}
1	4	4
2	1	2
2	5	2
2	6	2
3	2	2
4	3	3

TABLE 6: Small dataset results of the base LSSP MILP: lot sizing, inventories, coverage, stockout, and backorders.

k	t	X_{kt}	Xnp_{kt}	X'_{kt}	ST_{kt}	INV_{kt}	B_{kt}
1	1	48	0	48	2	21	0
1	2	27	0	27	0	25	0
1	3	0	0	0	0	1	0
2	1	0	0	0	33	1	35
2	2	48	0	48	30	1	21
2	3	48	0	48	0	1	4
3	1	72	0	72	0	39	0
3	2	0	0	0	11	19	0
3	3	0	0	0	0	1	12
4	1	0	0	0	14	1	30
4	2	0	0	0	32	1	45
4	3	96	0	96	0	19	0
5	1	48	0	48	8	31	0
5	2	41	0	41	0	33	0
5	3	0	0	0	0	1	0
6	1	48	0	48	19	15	0
6	2	48	0	48	5	29	0
6	3	0	0	0	0	1	6

TABLE 7: Small dataset results of the base LSSP MILP: scheduling.

i	j	t	SA_{ijt}	S_{ijt}	TP_{ijt}
1	2	1	1	1	24
1	2	2	0	1	24
1	1	3	1	1	24
2	4	1	1	1	24
2	3	2	1	1	24
2	3	3	0	1	24

machines, all the available capacity is occupied in the three defined periods. Notwithstanding, demand was higher than the available capacity, and therefore, the model had to delay the demand of products $k = 2, 3, 4$. Figure 3 shows the Gantt chart showing the schedule obtained after applying the base MILP model. Each row represents a machine i, and each rectangle a tool j; inside the rectangle, we have indicated the parts k and processing time t of each tool j.

The input data for the extended LSSP model are presented at https://bit.ly/3iA5hfq, and it is characterized by considering 2 machines, 4 tools, 6 parts, 3 periods, and 4 type operators. The results obtained with the decision variables in the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators are presented in Tables 8 and 9.

According to the obtained results, all the available capacity is occupied along the three defined periods.

Nevertheless, demand was higher than the available capacity, and therefore, the model had to delay the demand of both product $k = 2, 3, 4, 6$. The solution provided in the scheduling shows that the two type operators l are assigned to change the tools j.

The experimental results obtained with the tests performed for all the datasets employed in the validation for both the base model (Table 10) and the extended model in which the labor index is added (Table 11) are provided below. Four instances are generated of each dataset size. The synthetic instances have been generated through the previously proposed generator: https://bit.ly/3iwfObA.

The computational results (Table 10) show that the MILP model for lot sizing and scheduling on parallel flexible injection machines in small (S1, S2, S3, and S4) and medium (M1, M2, M3, and M4) instances achieve optimal results (GAP = 0%) in, at maximum, 12.6 seconds. With regards to the large instances generated (L1, L2, L3, and L4), the calculation time on average is set as 3.3 hours finding a near optimal solution, with an average 0.52% GAP. In this regard, it is worth highlighting that the large dataset L1 achieves the optimal solution in a very reduced computational time of 44 seconds.

The computational results (Table 11) show that the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators in small (S1, S2, S3, and S4) and medium (M1, M2, M3, and M4)
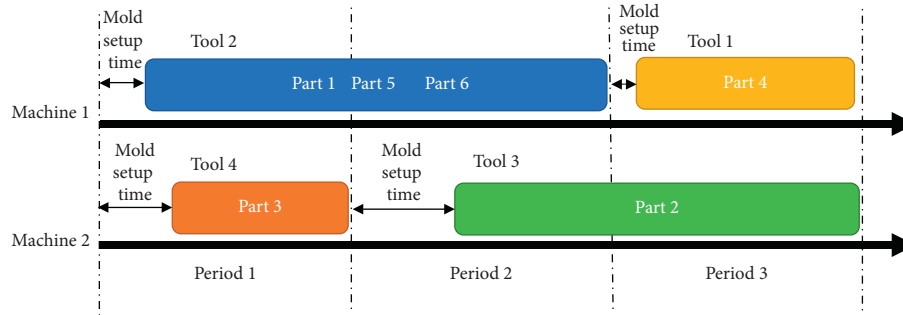
FIGURE 3: Gantt chart base MILP model for lot sizing and scheduling on parallel flexible injection machines.

TABLE 8: Small dataset results of the extended LSSP MILP, with setup common operators: lot sizing, inventories, coverage, stockout, and backorders.

k	t	X_k	Xnp_{kt}	X'_{kt}	ST_{kt}	INV_{kt}	B_{kt}
1	1	48	0	48	2	21	0
1	2	27	0	27	0	25	0
1	3	0	0	0	0	1	0
2	1	0	0	0	33	1	35
2	2	48	0	48	30	1	21
2	3	48	0	48	0	1	4
3	1	72	0	72	0	39	0
3	2	0	0	0	11	19	0
3	3	0	0	0	0	1	12
4	1	0	0	0	14	1	30
4	2	0	0	0	32	1	45
4	3	96	0	96	0	19	0
5	1	48	0	48	8	31	0
5	2	41	0	41	0	33	0
5	3	0	0	0	0	1	0
6	1	48	0	48	19	15	0
6	2	48	0	48	5	29	0
6	3	0	0	0	0	1	6

TABLE 9: Small dataset results of the base LSSP MILP: scheduling.

i	l	j	t	S_{iljt}	SA_{iljt}	TP_{ijt}
1	1	2	1	1	1	24
1	2	2	1	1	1	24
1	1	2	2	1	0	24
1	2	2	2	1	0	24
1	1	1	3	1	1	24
1	2	1	3	1	1	24
2	1	4	1	1	1	24
2	2	4	1	1	1	24
2	1	3	2	1	1	24
2	2	3	2	1	1	24
2	1	3	3	1	0	24
2	2	3	3	1	0	24

instances achieve optimal results (GAP = 0%) in, at maximum, 77.7 seconds. With regards to the large instances generated (L1, L2, L3, and L4), the calculation time on average is set as 2.8 hours finding a very near optimal solution, with an average 3% GAP. In this regard, it is worth

highlighting that the large dataset L1 achieves the optimal solution in a very reduced computational time of 208.83 seconds.

The experiments carried out for both the base model and the extended model that consider common setup operators

TABLE 10: Experimental results for the MILP model for lot sizing and scheduling on parallel flexible injection machines.

Dataset	I	J	K	T	Number of constraints	Number of variables	Number of binary variables	Number of integer variables	Number of continuous variables	Number of nonzeros	Objective value	Termination condition	Time (sec)	GAP (%)
S1	2	4	6	3	253	180	48	48	84	548	30699918	Optimal	0.15767312	0.00
S2	4	6	8	3	529	360	144	144	72	1240	13400191	Optimal	0.13881159	0.00
S3	6	8	16	3	1037	720	288	288	144	2672	11100467	Optimal	0.13907146	0.00
S4	8	10	22	3	1617	1116	480	480	156	4372	8100579	Optimal	0.13229871	0.00
M1	10	12	24	14	10882	7056	3360	3360	336	29232	75400153.9	Optimal	12.6211112	0.00
M2	12	14	28	14	14630	9408	4704	4704	0	39872	162199368	Optimal	11.8187988	0.00
M3	14	16	32	14	18930	12096	6272	6272	−448	52160	129000642	Optimal	6.2376368	0.00
M4	16	18	36	14	23782	15120	8064	8064	−1008	66096	109300097	Optimal	12.3485208	0.00
L1	18	20	40	14	29186	18480	10080	10080	−1680	81680	226999024	Optimal	44.0416777	0.00
L2	20	40	60	14	61754	38640	22400	22400	−6160	164880	698898867	maxTimeLimit	10801.9226	0.53
L3	25	45	70	14	85269	53130	31500	31500	−9870	230910	889697348	maxTimeLimit	18000.7021	1.23
L4	30	50	80	21	169221	104580	63000	63000	−21420	462680	764199835	maxTimeLimit	18025.0699	0.32

TABLE 11: Experimental results for the MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators.

Dataset	I	J	K	L	T	Number of constraints	Number of variables	Number of binary variables	Number of integer variables	Number of continuous variables	Number of nonzeros	Objective value	Termination condition	Time (sec)	GAP (%)
S1	2	4	6	2	3	392	228	96	96	36	880	30700163	Optimal	0.09	0.00
S2	4	6	8	2	3	904	504	288	288	−72	2224	9700582	Optimal	1.41	0.00
S3	6	8	16	2	3	1760	1008	576	576	−144	4736	23500652	Optimal	0.16	0.00
S4	8	10	22	2	3	2800	1596	960	960	−324	7860	18901051	Optimal	0.16	0.00
M1	10	12	24	4	14	36744	17136	13440	13440	−9744	100032	67803541	Optimal	19.20	0.00
M2	12	14	28	4	14	50596	23520	18816	18816	−14112	138992	99203043	Optimal	13.08	0.00
M3	14	16	32	4	14	66656	30912	25088	25088	−19264	184320	143003146	Optimal	39.02	0.00
M4	16	18	36	4	14	84924	39312	32256	32256	−25200	236016	146304008	Optimal	77.73	0.00
L1	18	20	40	6	14	156200	68880	60480	60480	−52080	432320	211505838	Optimal	208.83	0.00
L2	20	40	60	8	14	454244	195440	179200	179200	−162960	1212080	878439687	maxTimeLimit	10816.94	3.05
L3	25	45	70	12	14	950246	399630	378000	378000	−356370	2545660	912365839.8	maxTimeLimit	18032.57	4.47
L4	30	60	120	15	14	1893720	791280	756000	756000	−720720	5256960	1367518374	maxTimeLimit	10901.30	5.11

are valid for their application on solving LSSP models with real amount of data managed by real-world enterprises.

7. Discussion and Conclusions

This article addresses the LSSP applied to an automotive plastic components' enterprise. An MILP base model is proposed to deal with the lot-sizing and scheduling problem on parallel flexible injection machines to mainly minimize the setup, inventory, stockout, and backorder costs by taking into account injection molds as the main index to schedule parallel flexible injection machines. The MILP base model is extended to provide the enterprise under study with a more realistic solution that considers setup common operators. Therefore, the extended LSSP model, an MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators, is presented. This produces a model that adapts to the restrictions of the company under study, an automotive plastic components enterprise. The peculiarity of this model is that it takes injection molds as the main index to schedule parallel flexible injection machines by considering setup common operators. The novelty of both proposed models lies in our study considering many periods when modeling and running experiments to solve the LSSP. Moreover, the proposed MILP bears in mind stock coverage constraints, which are typical in the studied automotive supply chain industry context, and contemplates an objective function that allows idle times among molds, which is a fundamental characteristic for real cases and has been ignored by former studies.

Finally, this article validates the proposed MILP by performing experiments with different sized instances, including small, medium, and large datasets. The large dataset is characterized by replicating the amount of data used in the real enterprise that is the object of this study. The goodness of the model is evaluated with the computational time and the deviation of the obtained results as regards to the optimal solution.

This study is not without its limitations. The small and medium datasets are solved in both cases in very efficient computing times. The application of the proposed model using the large dataset is more limited in computational efficiency terms. To solve this problem, the literature indicates the generation of heuristics, metaheuristics, and matheuristics. This last type falls within the authors' future research options as far as the contemplated model herein is concerned. Thus, the first research line intends to improve the computational efficiency to solve the model by applying matheuristics, which would consist in solving the binary variables in both the base model base (S_{ijt} and SA_{ijt}) and its extended version (S_{iljt} and SA_{iljt}) by a metaheuristic technique, e.g., genetic algorithms, taboo search, and simulated annealing. The metaheuristics result will be provided as input data for the MILP. The following research lines focus on improving the model by considering new constraints that will be very useful for the real firm. In this way, the second future research line is a second extension of the base model that bears in mind the availability of materials. For this purpose, inventory equations are to be added that consider the list of materials needed to manufacture end products. Finally, for the third future research line, a third extension of the model is proposed by considering space limitations in a warehouse's volume. In this way, part volumes are calculated to meet both stock coverage and limited warehouse space, contemplated from the premise that all parts have different volume requirements. This means that the model and its third extension (or third-generation) will be capable of meeting the stock coverage of large-sized parts and stocking small-sized ones so that when they have to be produced, the production resources related to bigger pieces will be used. The third-generation model will allow bigger-sized parts to be stored, which will be left at the stock coverage level by calculating the quantity of smaller parts whose coverage can be extended.

Data Availability

The instances generated and analyzed during the study are available at (1) the base LSSP model, an MILP model for lot sizing and scheduling on parallel flexible injection machines: https://bit.ly/3p3IFqo. (2) The extended LSSP model, an MILP model for lot sizing and scheduling on parallel flexible injection machines with setup common operators: https://bit.ly/3iA5hfq. The algorithm developed for generating the synthetic datasets is available at https://bit.ly/3iwfObA.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Acknowledgments

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